Cognitive Sensing Based on Side Information

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***Abstract*— We study a sensing algorithm for cognitive radios based on Bayesian energy detection while utilizing available side information. The side information available to the cognitive user can consist of: (i) spatial locations of the cognitive and primary receivers, (ii) received power of the primary-signal at the cognitive user, and (iii) a priori transmission probability of the primary user. Considering several scenarios with different combinations of side information, we derive the respective, optimal detection thresholds for the cognitive user. Numerical results using these thresholds show significant performance improvement based on the side information. Specifically, information on spatial locations can help stabilize the performance for a wide range of the primary activity factor. Highly skewed a priori primary-transmission probability further helps improve the performance dramatically.**

I. Introduction

According to the FCC (Federal Communications Commission) recent report on spectrum utilization [1], measurement data shows that licensed frequency bands are heavily under-utilized. As a way of making more efficient use of the limited frequency resource, researchers have been studying cognitive radios, devices that can adapt their operating characteristics to the channel condition, as a candidate for secondary spectrum access.

In order for a cognitive radio to transmit its own information without creating inhibiting interference to the licensed (primary) users, an important requirement is for it to successfully sense an idle channel in a particular frequency band. A popular method for detecting the primary user's signal is energy detection, which measures the received signal power and makes a decision on the channel occupancy based on a Bayesian estimate. This kind of detector has been considered as the decision rule for the spectrum vacancy because it is very simple and does not require the knowledge on the primary users signal structure. There have been extensive studies on this detection method. The simplest energy detection of unknown deterministic signal in AWGN channel is studied in [2]. In [3], performance of energy detection in a multipath channel is analyzed. Collaboration among the secondary users is recently proposed to improve the performance of spectrum sensing in [4], [5]. A cross-layer spectrum sensing and access policy are proposed and analyzed in [6]. In particular, the fundamental limit of energy detectors is studied in [7].

In most previous research, performance of the energy detector is studied mainly in terms of a given *false alarm probability*, *miss detection probability* or *collision probability*. Research on determining the detection threshold, however, has rarely been done. In addition, if the cognitive users have some side information about the primary users, they can use this information in setting the detection threshold to improve the performance of both the primary and secondary networks. Such side information can include spatial locations of the primary and secondary transmitter and receiver, the a priori probability of the primary user's transmission, or both. As an example, at some time periods, (e.g. around 3 a.m.), there may be little possibility that the primary users are active, which means the secondary users can access the spectrum more aggressively. As another example, given the same miss detection probability, the interference at the primary receiver would be different depending on the distance from the secondary transmitter.

In this paper, we study a cognitive sensing scheme based on Bayesian energy detection that utilizes side information. The sensing threshold is set as a total cost consisting of the interference caused from the secondary transmitters when the spectrum is in-use and the transmission opportunity loss experienced by the secondary users not operating when the spectrum is idle. Depending on the available side information about the users locations and/or a priori primary-transmission probability, we derive the detection threshold minimizing the total cost. Numerical comparisons illustrate the gain obtained by utilizing the side information.

This paper is organized as follows. In Section II, we set up the problem by introducing the network and channel models. In Section III, we describe the sensing algorithms for various side information scenarios. Section IV presents the numerical results illustrating the performance of these algorithms. We provide some concluding remarks in Section V.

II. Problem Setup

A. Network Configuration

Consider a network whose elements are located in a circular region, in which a single primary Tx-Rx pair and a single secondary Tx-Rx pair exist. The primary Rx is located at the center of the disc with radius R_p. The primary Tx is located within the disc with uniform probability. Let its location be $P_{tx} = (s_p, \theta_p)$ in the polar coordinate system. The secondary Tx is also randomly placed within the disc at location $S_{tx} = (s_{pc}, \theta_{pc})$. Its corresponding Rx location is $S_{rx} = (s_c, \theta_c)$ relative to the secondary Tx. The secondary Tx and Rx can communicate provided they are less than R_c apart ($s_c \leq R_c$) (see Fig. 1).

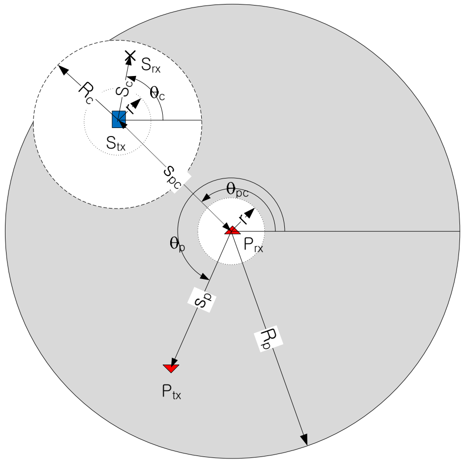

Fig. 1. Network Configuration.

We also assume a protected region, defined as a disc of radius r centered at the primary tx and secondary rx with no other radios inside. This region is to exclude the possibility that two interfering radios are placed at the same location. In Fig. 1, the circles centered at the primary Rx and the secondary Tx with radius r are the protected regions.

B. Signal and Channel Models

We consider a fading channel with path loss. For a Tx-Rx pair with distance d between them, denote the channel as h, then

$$h \sim \mathcal{CN}(0, \sigma_h^2), \tag{1}$$

where channel variance σ_h^2 is a function of the pathloss as

$$\sigma_h^2 = \frac{A}{d^\alpha}. \tag{2}$$

Here A is a constant dependent on the frequency, and α is the pathloss exponent. Without loss of generality, we assume $A = 1$.

Let the transmit power of the primary user be P and that of the cognitive user be P_c. Similar to conventional energy detectors, the cognitive user needs to perform a hypothesis testing to decide between the following two hypotheses:

$$\mathcal{H}_0 \quad : \quad y = z \tag{3}$$
$$\mathcal{H}_1 \quad : \quad y = x + z \tag{4}$$

where x is the complex signal received at the secondary user from the primary Tx after experiencing path loss and fading, and z is the thermal noise. They both have complex Gaussian distributions as

$$x \quad \sim \quad \mathcal{CN}(0, P\sigma_h^2) \tag{5}$$
$$z \quad \sim \quad \mathcal{CN}(0, \sigma_z^2), \tag{6}$$

where σ_h^2 is given in (2) and the noise power σ_z^2 is fixed.

III. Cognitive Sensing Based on Energy Detection

The cognitive Tx-Rx pair should operate in such a way to minimize the interference to the primary Rx while fully utilizing the frequency band at primary-idle times. This objective can be accomplished by setting the threshold γ to minimize the following cost function:

$$J = \int \cdots \int \Big(\underbrace{I_{pc}(s_{pc}) \Pr(\mathcal{H}_0|\mathcal{H}_1, \gamma) \Pr(\mathcal{H}_1)}_{\text{Interference}} + \underbrace{I_c(s_c) \Pr(\mathcal{H}_1|\mathcal{H}_0, \gamma) \Pr(\mathcal{H}_0)}_{\text{Transmission Opportunity Loss}} \Big) \cdot f(s_c, \theta_c, s_{pc}, \theta_{pc}, s_p, \theta_p)\, ds_c\, d\theta_c\, ds_{pc} d\theta_{pc} ds_p d\theta_p \tag{7}$$

where

- $\Pr(\mathcal{H}_0|\mathcal{H}_1, \gamma)$ and $\Pr(\mathcal{H}_1|\mathcal{H}_0, \gamma)$ are the *Miss Detection Probability* (P_{MD}) and *False Alarm Probability* (P_{FA}), conditioned on the detection threshold γ, respectively.
- $\Pr(\mathcal{H}_1)$ is the probability of the primary user transmitting, and $\Pr(\mathcal{H}_0) = 1 - \Pr(\mathcal{H}_1)$. Denote $\lambda_1 = \Pr(\mathcal{H}_1)$.
- $I_{pc}(s_{pc})$ is the *potential* interference to the primary Rx caused by the cognitive Tx when it misses the primary Tx's signal, and $I_c(s_c)$ is the link quality between the cognitive Tx and Rx pair. These two quantities can be written as

$$I_{pc}(s_{pc}) \quad = \quad P_c s_{pc}^{-\alpha} \tag{8}$$
$$I_c(s_c) \quad = \quad P_c s_c^{-\alpha} \tag{9}$$

  where P_c is the transmit power of the cognitive user and α is the path loss exponent.
- $f(s_c, \theta_c, s_{pc}, \theta_{pc}, s_p, \theta_p)$ is the joint density function of the location parameters.

The detection threshold γ can be determined by minimizing J based on available side information. In this paper, we consider side information as some combinations of the following values:

- σ_x^2: the power of the received primary-signal at the cognitive radio. From Eqs. (2) and (5), σ_x^2 depends on (s_{pc}, θ_{pc}) and (s_p, θ_p) as

$$\sigma_x^2 = P\left(s_p^2 + s_{pc}^2 - 2 s_p s_{pc} \cos(\theta_p - \theta_{pc})\right)^{-\alpha/2} \tag{10}$$

- σ_z^2: the thermal noise power
- λ_1: the a priori probability of the primary user transmitting ($\lambda_1 = \Pr(\mathcal{H}_1)$).
- the locations $S_{tx} = (s_{pc}, \theta_{pc})$ and $S_{rx} = (s_c, \theta_c)$.

In the following subsections, we will determine the detection threshold to minimize the cost function in Eq. (7) for various side-information scenarios.

A. When $\sigma_x^2, \sigma_z^2, S_{tx}, S_{rx}, \lambda_1$ are available

In this case, the cognitive transmitter knows the locations of both its cognitive receiver and the primary receiver. These locations determine the statistics of the received primary-signal at the cognitive Tx.

Given the location $S_{tx} = (s_{pc}, \theta_{pc})$, $S_{rx} = (s_c, \theta_c)$, and σ_x^2, minimizing the cost function in (7) is equivalent to minimizing the following simplified cost:

$$\begin{aligned} J_0 &= I_{pc}(s_{pc}) \Pr(\mathcal{H}_0|\mathcal{H}_1, \gamma) \Pr(\mathcal{H}_1) \\ &+ I_c(s_c) \Pr(\mathcal{H}_1|\mathcal{H}_0, \gamma) \Pr(\mathcal{H}_0) \end{aligned} \tag{11}$$

Here J_0 is the *Bayes Risk* with the costs of $I_{pc}(s_{pc})$ and $I_c(s_c)$ assigned to the miss detection and false alarm errors, respectively. With side information σ_z^2 and λ_1, the optimal decision rule is

$$\frac{\Pr(y|\mathcal{H}_1) \Pr(\mathcal{H}_1) I_{pc}(s_{pc})}{\Pr(y|\mathcal{H}_0) \Pr(\mathcal{H}_0) I_c(s_c)} \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} 1 \tag{12}$$

$$\iff \frac{\frac{1}{\sqrt{2\pi(\sigma_x^2+\sigma_z^2)}} \exp^{-\frac{y^2}{2(\sigma_x^2+\sigma_z^2)}}}{\frac{1}{\sqrt{2\pi\sigma_z^2}} \exp^{-\frac{y^2}{2\sigma_z^2}}} \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \frac{1-\lambda_1}{\lambda_1} \frac{I_c(s_c)}{I_{pc}(s_{pc})}.$$

The Log-Likelihood Ratio (LLR) can then be computed as

$$\begin{aligned} &T(x) = x^2 \\ &\underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \frac{\sigma_z^2}{\sigma_x^2}(\sigma_x^2 + \sigma_z^2) \left[\frac{1}{2} \ln \left(1 + \frac{\sigma_x^2}{\sigma_z^2} \right) + \ln \frac{1-\lambda_1}{\lambda_1} - \ln \rho(s_{pc}, s_c) \right] \end{aligned}$$

where

$$\rho(s_{pc}, s_c) \triangleq \frac{I_{pc}(s_{pc})}{I_c(s_c)} = \left(\frac{s_{pc}}{s_c} \right)^{-\alpha}. \tag{13}$$

Denote

$$\sigma^2 = \frac{\sigma_z^2}{\sigma_x^2}(\sigma_x^2 + \sigma_z^2), \tag{14}$$

this leads to the optimal detection threshold as

$$\gamma_0 \triangleq \sigma^2 \left[\frac{1}{2} \ln \left(1 + \frac{\sigma_x^2}{\sigma_z^2} \right) + \ln \frac{1-\lambda_1}{\lambda_1} + \alpha \ln \frac{s_{pc}}{s_c} \right]. \tag{15}$$

With the given side information, the optimal detection threshold γ_0 depends on the distance between the cognitive Tx and the primary Rx (S_{pc}), the distance between the cognitive Tx and Rx (S_c), as well as the a priori probability λ_1. As the cognitive Tx approaches closer to the primary Rx, it should decrease the threshold so that the miss detection probability decreases. This is intuitively appealing because the cognitive Tx may cause more interference to the primary Rx due to miss-detection as it comes closer. On the contrary, as the cognitive Tx moves away from the primary Rx, the threshold should be increased so that the false alarm probability decreases. In this latter case, the losses for the cognitive user from missing the transmission opportunities are more important than the interference caused to the primary Rx.

In some cases, γ_0 can be negative, which always makes the detector decide in favor of $\mathcal{H}_1$. Thus we can set the threshold as

$$\Gamma = \max(0, \gamma_0) \tag{16}$$

The detection performance can be analyzed by noting that

$$\frac{T(x)}{\sigma_z^2/2} \sim \chi_2^2 \text{ under } \mathcal{H}_0 \tag{17}$$

$$\frac{T(x)}{(\sigma_x^2 + \sigma_z^2)/2} \sim \chi_2^2 \text{ under } \mathcal{H}_1. \tag{18}$$

The false-alarm probability P_{FA} of the detector therefore is

$$\begin{aligned} \Pr(\mathcal{H}_1|\mathcal{H}_0) &= \Pr(T(x) > \Gamma|\, \mathcal{H}_0) \\ &= \Pr\left(\frac{T(y)}{\sigma_z^2/2} > \frac{\Gamma}{\sigma_z^2/2} \middle| \mathcal{H}_0 \right) \\ &= \exp\left(-\frac{\Gamma}{\sigma_z^2} \right), \end{aligned} \tag{19}$$

and the miss-detection probability P_{MD} is

$$\begin{aligned} \Pr(\mathcal{H}_0|\mathcal{H}_1) &= \Pr(T(x) < \Gamma|\mathcal{H}_1) \\ &= \Pr\left(\frac{T(x)}{(\sigma_x^2 + \sigma_z^2)/2} > \frac{\Gamma}{(\sigma_x^2 + \sigma_z^2)/2} \middle| \mathcal{H}_1 \right) \\ &= 1 - \exp\left(-\frac{\Gamma}{\sigma_x^2 + \sigma_z^2} \right). \end{aligned} \tag{20}$$

B. When $\sigma_x^2, \sigma_z^2, S_{tx}, \lambda_1$ are available

In this case, the cognitive transmitter knows the location of the primary receiver but not its own (cognitive) receiver. Then in the cost function (7), we need to perform the integration over all possible cognitive Rx locations S_{rx}, which is independent of the known S_{tx} and P_{tx}. Minimizing J in (7) is then equivalent to minimizing

$$\begin{aligned} J_1 &= \int_r^{R_c} \int_{-\pi}^{+\pi} J_0 f(s_c, \theta_c)\, d\theta_c\, ds_c \\ &= I_{pc}(s_{pc}) \Pr(\mathcal{H}_0|\mathcal{H}_1, \gamma) \Pr(\mathcal{H}_1) + \overline{I}_c \Pr(\mathcal{H}_1|\mathcal{H}_0, \gamma) \Pr(\mathcal{H}_0) \end{aligned} \tag{21}$$

where

$$f(s_c, \theta_c) = \frac{2s_c}{R_c^2 - r^2} \cdot \frac{1}{2\pi} \tag{22}$$

and

$$\begin{aligned} \overline{I}_c &= \int_r^{R_c} \int_{-\pi}^{+\pi} P_c s_c^{-\alpha} f(s_c, \theta_c)\, d\theta_c\, ds_c \\ &= \begin{cases} \dfrac{2R_Y}{R_c^2 - r^2} \ln(R_c/r) & \alpha = 2, \\ \dfrac{2R_Y}{2-\alpha} \dfrac{R_c^{2-\alpha} - r^{2-\alpha}}{R_c^2 - r^2} & \alpha \neq 2. \end{cases} \end{aligned} \tag{23}$$

Minimizing J_1 leads to the following optimal detection threshold:

$$\begin{aligned} \gamma_1 &= \sigma^2 \left[\frac{1}{2} \ln \left(1 + \frac{\sigma_x^2}{\sigma_z^2} \right) + \ln \frac{1-\lambda_1}{\lambda_1} - \ln \frac{I_{pc}(s_{pc})}{\overline{I}_c} \right] \\ &= \sigma^2 \left[\frac{1}{2} \ln \left(1 + \frac{\sigma_x^2}{\sigma_z^2} \right) + \ln \frac{1-\lambda_1}{\lambda_1} + \alpha \ln s_{pc} + \ln \tilde{I}_c \right], \end{aligned} \tag{24}$$

where $\tilde{I}_c = \overline{I}_c / P_c$ and σ^2 is given in (14).

Again the threshold for this case depends on the distance between the cognitive Tx and the primary Rx (S_{pc}), which affects σ_x^2 (10). As the cognitive Tx moves away from the primary Rx, the threshold is increased. This is because the interference signal power at the primary Rx is reduced, thus the cognitive user can afford to increase the miss detection probability, while decreasing its false-alarm probability. Here, however, because S_{rx} is unknown, the uncertainty on the location of the cognitive Rx is reflected in the last term, $\ln \tilde{I}_c$, which is always negative. Instead of using the precise location s_c as in the threshold γ_0 (15), the term $\ln \tilde{I}_c$ in γ_1 (24) captures the average effect over all possible cognitive Rx locations.

C. When $\sigma_x^2, \sigma_z^2, S_{rx}, \lambda_1$ are available

Opposite to the second scenario, here the cognitive Tx knows the location of its own (cognitive) Rx, but not the location of the primary Rx. Similarly, though, the optimal threshold can be obtained by taking the expectation of J_0 in (11) over all S_{tx} locations as

$$J_2 = \int_r^{R_p} \int_{-\pi}^{+\pi} J_0 \Pr(s_{pc}, \theta_{pc})\, d\theta_{pc}\, ds_{pc} \tag{25}$$
$$= \overline{I}_{pc} \Pr(\mathcal{H}_0|\mathcal{H}_1,\gamma) \Pr(\mathcal{H}_1) + I_c(s_c) \Pr(\mathcal{H}_1|\mathcal{H}_0,\gamma) \Pr(\mathcal{H}_0)$$

where

$$\overline{I}_{pc} = \begin{cases} \dfrac{2R_Y}{R_p^2 - r^2} \ln(R_p/r) & \alpha = 2, \\ \dfrac{2R_Y}{2-\alpha} \dfrac{R_p^{2-\alpha} - r^{2-\alpha}}{R_p^2 - r^2} & \alpha \neq 2. \end{cases} \tag{26}$$

The optimal detection threshold now becomes

$$\gamma_2 = \sigma^2 \left[\frac{1}{2} \ln \left(1 + \frac{\sigma_x^2}{\sigma_z^2} \right) + \ln \frac{1-\lambda_1}{\lambda_1} - \ln \frac{\overline{I}_{pc}}{I_c(s_c)} \right] \tag{27}$$
$$= \sigma^2 \left[\frac{1}{2} \ln \left(1 + \frac{\sigma_x^2}{\sigma_z^2} \right) + \ln \frac{1-\lambda_1}{\lambda_1} - \ln \tilde{I}_{pc} - \alpha \ln s_c \right],$$

where $\tilde{I}_{pc} = \overline{I}_{pc}/P_c$ and σ^2 is given in (14).

As in the first scenario, the threshold increases as the cognitive Rx approaches its Tx so that the false alarm probability decreases. This is to reduce the transmission opportunity loss, which would, otherwise, be high when the cognitive Tx-Rx pair is close. The lack of information on the distance between the cognitive Tx and the primary Rx is reflected in the average term, $-\ln \tilde{I}_{pc}$, which is always positive in this case.

D. When $\sigma_x^2, \sigma_z^2, \lambda_1$ are available

In this case, no location information is available to the cognitive Tx (either of the cognitive Rx or the primary Rx). Based on the optimal threshold for previous scenarios in (24) and (27), the detection threshold now can be written as

$$\gamma_3 = \sigma^2 \left[\frac{1}{2} \ln \left(1 + \frac{\sigma_x^2}{\sigma_z^2} \right) + \ln \frac{1-\lambda_1}{\lambda_1} - \ln \frac{\overline{I}_{pc}}{\overline{I}_c} \right] \tag{28}$$
$$= \sigma^2 \left[\frac{1}{2} \ln \left(1 + \frac{\sigma_x^2}{\sigma_z^2} \right) + \ln \frac{1-\lambda_1}{\lambda_1} - \ln \tilde{I}_{pc} + \ln \tilde{I}_c \right].$$

This threshold uses the average information about both the locations of the primary and cognitive Rx's.

E. When λ_1 is NOT available

For the corresponding cases when λ_1 is unavailable, it is easy to show that the detection thresholds can be obtained by setting $\lambda_1 = 0.5$ respectively in (15), (24), (27) and (28).

IV. Numerical Results

For the simulations, as depicted in Fig. 1, the primary Rx is located at the center of the circle with radius R_p. The primary Tx and the cognitive Tx are within this circle with uniform distributions. The cognitive Rx is placed within a circle of radius R_c centered at the generated cognitive Tx location. We use the following values in the simulations: $R_p = R_c = 10, r = 1, \alpha = 2.1$. The primary Tx transmits its signal with probability λ_1 and with power $P = \sigma_z^2 \cdot R_p^\alpha$, making the mean SNR at the cell edge 0 dB. The transmit power of the cognitive Tx is set to be $P_c = \sigma_z^2 \cdot R_c^\alpha$ for the same reason. We repeat random generations of the locations for 30,000 times and perform the energy detection 1,000 times for each set of locations. For comparison, we also included performance of the standard *Constant False Alarm Detector* (CFAR) [8] with $P_{FA} = 0.001$ and 0.01, without any side information except σ_z^2.

In Fig. 2-4, we compare the cases in which no a priori primary-transmission probability λ_1 is available to the cognitive user. The cognitive user can then use only side information about spatial locations. Fig. 2 shows the total costs in (7) of the detectors. The results are plotted against $\Pr(\mathcal{H}_1)$. These plots show that information on the spatial locations helps improve detector performance. The detector with all location information on both S_{tx} and S_{rx} performs the best, while the detector with the information on either S_{tx} or S_{rx} are comparable in the performance. These three detectors performance depends little on the (unknown) primary activity factor λ_1. The performance of the standard CFAR, on the other hand, depends heavily on the activity factor λ_1. This means that CFAR could hardly control the system performance in the cognitive networks. The detector without any location information, using only σ_x^2 and σ_z^2, shows performance also highly dependent on λ_1. Comparison shows that information on spatial locations not only stabilizes performance but also improve it (in terms of the cost function J in (7)) between 1.5 to 3 times, depending on the primary activity factor and the specific spatial information available.

Fig. 3 and Fig. 4 respectively show the corresponding interferences and the transmission opportunity losses of the studied detectors. They show interesting behavior of the detectors with the knowledge of either S_{tx} or S_{rx}. For the detector knowing S_{tx}, the transmission opportunity loss is as low as that of the detector knowing both locations, but the interference is higher compared to the other detectors with location knowledge. The detector with S_{rx} creates as low an interference as the detector with both locations, but its transmission opportunity loss is higher than the other location-aware detectors and even higher than the detector without any location information.

Fig. 5 and Fig. 6 include the effect of knowledge on λ_1. Fig. 5 compares the cases when S_{tx} is unavailable, and Fig. 6 when S_{tx} is available. We observe that, when λ_1 is skewed ($\lambda_1 \neq 0.5$), then the knowledge of λ_1 can improve the detector performance dramatically, regardless of presence or lack of knowledge of location. The performance gain from knowing λ_1 increases as $|\lambda_1 - 0.5|$ increases.

V. Conclusion

In this paper, we have shown the benefits of side information in improving the performance of cognitive sensing algorithms based on the Bayesian energy detector. Side information helps in minimizing the detection cost consisting of the interference and the transmission opportunity loss. Specifically, we considered side information as the spatial locations of the cognitive

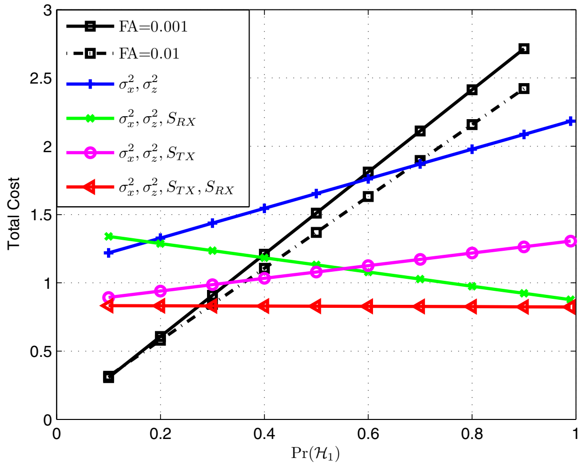

Fig. 2. Total Costs Comparison without knowledge of λ_1.

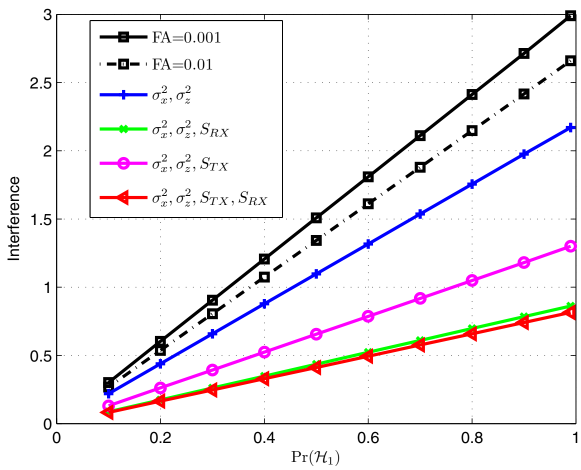

Fig. 3. Interference Comparison without knowledge of λ_1.

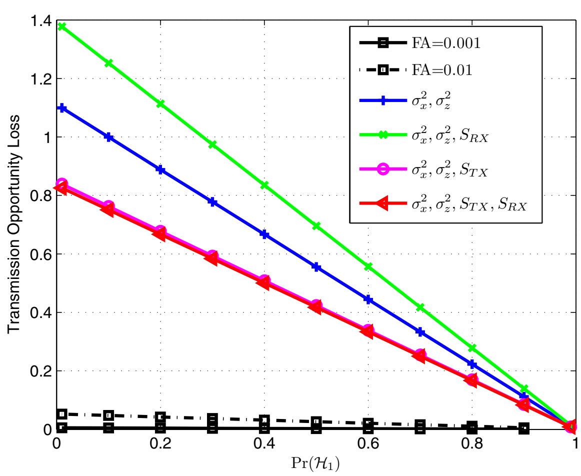

Fig. 4. Opportunity Loss Comparison without knowledge of λ_1.

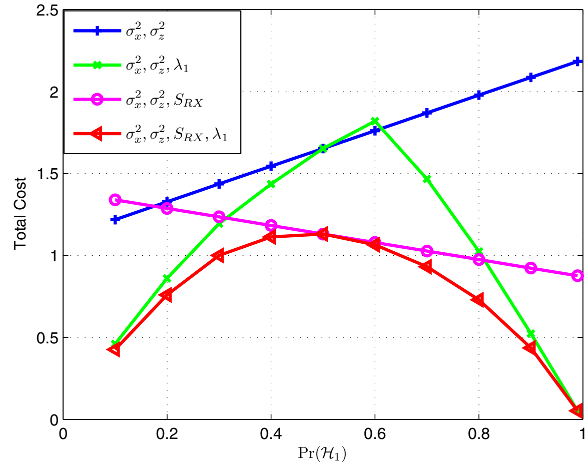

Fig. 5. Total Costs Comparison with knowledge of λ_1.

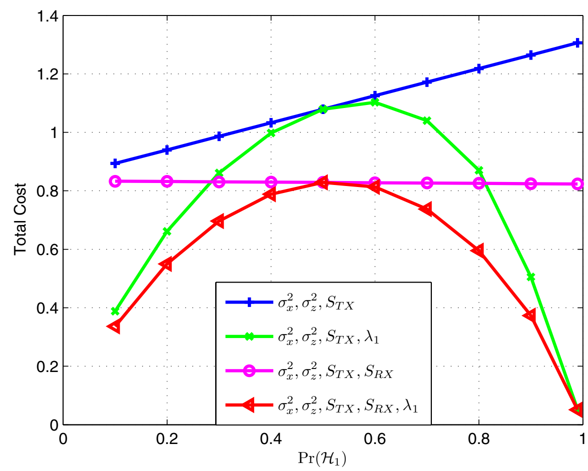

Fig. 6. Total Costs Comparison with knowledge of λ_1 and S_{tx}.

and primary receivers, the power of the primary user's signal received at the cognitive user, the noise variance and the a priori probability of the primary user's transmission. We derived the optimal detection thresholds given various combinations of the side information. Simulation results showed that the studied side information can significantly improve the sensing performance. The detector with information on both spatial locations and a priori primary-transmission probability performed the best. Specifically, the a priori primary-transmission probability helps produce a large gain when it is highly skewed (far from 0.5). Without the a priori primary-transmission probability, the detector with all location information exhibited the best and stable performance for wide range of unknown primary activity factor. Our studies showed that both spatial locations and a priori transmission probability are important factors in improving cognitive sensing performance.

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